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An Investigation of Forecasting Critical Spare Parts Requirement

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Abstract

The critical spare parts (CSP) is essential to machine operation, which is also more expensive, have longer purchasing lead time and larger demand variation than non-critical spare parts. When the equipment is operating, critical spare parts required to be changed due to wear and tear. Excessive critical spare parts will cause accumulation of the inventory and insufficiency will cause termination of machine operation, thereby leading to loss. Therefore, it is an important issue to devise a way to forecast the future required amount of CSP accurately.

This investigation applied grey prediction model, back-propagation network and moving average method to forecast the CSP requirement in a semiconductor factory, so as to effectively predict the required number of CSP, which can be provide as a reference of critical spare parts control.

1. Introduction

The critical spare parts in semiconductor are considerably expensive, the purchasing lead time is long, the demand variation is huge, and indispensably play important roles in factory operation. The prices of critical spare parts (CSP) are range from tens to hundreds of thousand dollars. As the equipments operate, some critical spare parts need to be replaced due to wear and tear. If appropriate amount of critical spare parts are not prepared, machines may not be able to function, thus resulting in a waste of resources. However, estimation of the critical spare parts consumption is a complicated subject. In addition to preparing the required CSP of the machines need according to the work orders, there are also other unpredictable factors, such as human factors or spare parts quality problems. Such a circumstance is more obvious in semiconductor industries. For this consideration, it is important to be able to effectively predict the required number of critical spare parts in advance.

This investigation focuses on forecasting the critical spare parts and presents a case study to evaluate the prediction performance of forecasting methods. Grey prediction model, back-propagation network (BPN) and moving average method (MA) are used to perform CSP demand prediction, so as to effectively predict the required number of CSP which can be provide as a reference of spare parts control.

2. Related Literatures

Although the spare parts requirement prediction and management is so important in industries, researches focus on demand forecasting of spare parts is still very under-developed, there are not many investigations focus on the CSP requirement prediction.

Prakash et al. [1] used analytic hierarchy process (AHP) method to evaluate the criticality of spare parts. Kabir [2] developed a simulation model to determine the optimal value of the decision variable by minimizing the total cost of replacement and inventory. Dekker [3] pointed out that spare parts can be classified into critical and non-critical demand, and proposed a stocking policy verified by simulation. Ghobbar [4] experimented 13 forecasting methods to predict spare parts demand for airline fleets. Aronis [5] calculated the required stock levels and determine the distributions of demand for spare parts by Bayesian approach. Caglar [6] investigated a spare parts inventory problem and formulated a model to minimize the inventory cost subjected to a response time constraint at each field depot.

Based on the above literatures, subject and research on spare parts management mostly focused on the consideration of safe inventory level. Investigations on the actual number of spare parts required are very rare. If the actual required number can be correctly predicted, there will be no problem of controlling inventory level and purchasing quantities. Hence, this

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investigation applied grey prediction model, BPN,MA to predict the critical spare parts requirement accurately and reduce the unnecessary costs and slack risks.

3. Research methods

Several methods have been employed to forecast the demand quantity of spare parts, and the grey prediction method and back-propagation network (BPN) have good prediction performance in many fields. Sheu and Kuo [7] apply grey prediction model to forecast the timing of prevent maintenance accurately. Lin and Yang [8] forecast accurately the output value of Taiwan's opto-electronics industry through grey forecasting model. Ansuj et al. [9] used time series models and BPN to predict the behaviors of sales, the result indicated BPN had better prediction performance than time series models. Law [10] utilized BPN to forecast the demand of tourism, the result indicated that the BPN has higher forecasting accuracy than time-series models, feed-forward neural networks, and regression models. Thus, this paper applied grey prediction model, BPN to forecast the demand of CSP.

The research framework of this paper is shown as Figure 1.

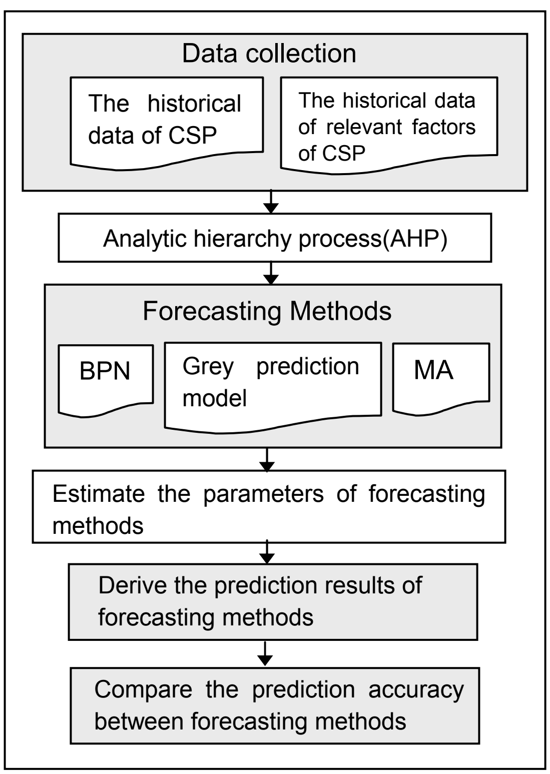

Figure 1. Research framework

At the beginning, the author will collect the raw data and applied analytic hierarchy process (AHP) to sieve out the more correlated factors, then input the data into grey prediction model, BPN MA, afterwards, the author will derive the prediction result and compare the prediction accuracy of each forecasting method.

3.1. Analytic hierarchy process

Analytic hierarchy process (AHP) was proposed by Thomas L. Satty in 1971, primarily applied to uncertainty and decision involving many evaluation rules. AHP makes use of pairwise comparisons, hierarchical structures, and 9-point ratio scaling to apply weights to attributes. In this study, the AHP was used to find out relevant factors of the CSP and determine the relative importance.

The three main steps of AHP are illustrated as follows:

Step 1: Construction of hierarchical structure.

Step 2: Calculation of weights between factors at each hierarchical level.

Step 3: Calculation of the overall hierarchical weights.

After calculating weights of every factor, further analysis and choice are made according to weights and significance represented by each factor.

3.2. Grey prediction model

The grey prediction method was developed by Deng [11] in 1982, and the GM(1,1) is the most frequently used grey prediction method. The objective of GM(1,1) is to find a sequence of each element corresponding to future dynamism, thereby developing prediction model.

The following symbols are used throughout GM(1,1):

n — The number of samples used in progressive predictive series.

a — The first parameter for Least-square method.

b — The second parameter for Least-square method.

$x^{(0)}(k)$ — The predicted progress of the measurement value. For example $\hat{x}^{(0)}(1)$ represents the predicted value of the prediction target for the first period, where $k=1,2,3,4.....n$.

$x^{(1)}(k)$ — The predicted progress of the measurement value in the k^{th} period for the first predictive series based on Accumulated Generating Operation (AGO),where $k=1,2,3,4...n$.

$Z^{(1)}(k)$ — The mean value of added trigger measurement value, where $k=1,2,3....n$.

where $Z^{(1)}(k)=0.5\,x^{(1)}(k)+x^{(1)}(k-1)$.

$Z^{(1)}(k)$ sequence is generated to smooth out the $x^{(1)}(k)$ sequence.

B The matrix of $Z^{(1)}(k)$.

Y_N A vector indicates incremental trigger measurement in a period.

$\hat{x}^{(0)}(k+1)$ The forecasted increment of the measurement for $k+1^{th}$ period in the 0^{th} predictive sequence.

$\hat{x}^{(1)}(k+1)$ The forecasted increment of the measurement for $k+1^{th}$ period in the 0^{th} predictive sequence using AGO.

The main steps of GM(1,1) are illustrated as follow:

1. Accumulated Generating Operation

An original sequence of data with n measurement is expressed as

$$x^{(0)}=\left\{x^{(0)}(1),x^{(0)}(2),x^{(0)}(3),\ldots,x^{(0)}(n)\right\}=\left(x^{(0)}(k);\ k=1,2,3,\ldots n\right) \quad (1)$$

The standard formula for the accumulated generating operation at the r^{th} accumulation is:

$$\left(x^{(r)}(k);\, r=1,2,3,\ldots,\, n\right)=\left(\sum_{m=1}^{k} x^{(r-1)}(m)\right) \quad (2)$$

Then, $x^{(0)}$ is made the first-order accumulated generating operation to obtain the number series.

$x^{(1)}=\{\, x^{(1)}(1),\, x^{(1)}(2), \ldots.., x^{(1)}(n)\}$

2. Find out $x^{(0)}(k)$, $Z^{(1)}(k)$.

Define the inverse accumulated generating operation (IAGO) as follows:

$$x^{(r-1)}(k) = x^{(r)}(k) - x^{(r)}(k-1) \quad (3)$$

when $r = 1$, then

$$x^{(0)}(k) = x^{(1)}(k) - x^{(1)}(k-1)$$

Find out

$$\frac{dx^{(1)}}{dt}=x^{(1)}(\Delta t+t)-x^{(1)}(t)=x^{(1)}(k)-x^{(1)}(k-1)=x^{(0)}(k)$$

Calculate: $Z^{(1)}(k) = x^{(1)}(k)$.

The GM (1,1) differential formula [12], that is:

$$\frac{dx}{dt}+ax^{(1)}=b$$

$$x^{(0)}(k) + aZ^{(1)}(k) = b,\ \ k = 2, \ldots, n. \quad (4)$$

3. Apply Least-square method to find out vender Y_N and the matrix B.

Substitute $k=2\ldots n$ into $x^{(0)}(k)+aZ^{(1)}(k)=b$, and express the result in the form of matrix $Y_N = B\,\hat{a}$ a to obtain Y_N, B.

$$Y_N=\begin{bmatrix} x^{(0)}(2)\\ x^{(0)}(3)\\ \vdots \\ x^{(0)}(n)\end{bmatrix};\quad B=\begin{bmatrix} -Z^{(1)}(2),1\\ -Z^{(1)}(3),1\\ \vdots \\ -Z^{(1)}(n),1\end{bmatrix}$$

$$\hat{a}=\begin{bmatrix} a\\ b\end{bmatrix}=\left(B^{T}B\right)^{-1}B^{T}Y_N; \quad (5)$$

4. Find out a and b.

$$a=\frac{\sum_{k=2}^{n} z^{(1)}(k)\sum_{k=2}^{n} x^{(0)}(k)-(n-1)\sum_{k=2}^{n} z^{(1)}(k)x^{(0)}(k)}{(n-1)\sum_{k=2}^{n}\left[z^{(1)}(k)\right]^2-\left[\sum_{k=2}^{n} z^{(1)}(k)\right]^2}, \quad (6)$$

$$b=\frac{\sum_{k=2}^{n}\left[z^{(1)}(k)\right]^2\sum_{k=2}^{n} x^{(0)}(k)-\sum_{k=2}^{n} z^{(1)}(k)\sum_{k=2}^{n} z^{(1)}(k)x^{(0)}(k)}{(n-1)\sum_{k=2}^{n}\left[z^{(1)}(k)\right]^2-\left[\sum_{k=2}^{n} z^{(1)}(k)\right]^2} \quad (7)$$

5. List

$$\hat{x}^{(1)}(k+1)=\left[x^{(0)}(k)-\frac{b}{a}\right]e^{-ak}+\frac{b}{a} \quad (8)$$

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)+\hat{x}^{(1)}(k)$$

Therefore, the prediction data can be expressed by combining Equation (6), (7) and (8) as

$$\hat{x}^{(0)}(k+1)=(1-e^{a})\left[x^{(0)}(1)-\frac{b}{a}\right]e^{-ak},\ k=1\sim n. \quad (9)$$

6. Forecasting the trigger measurement value for the subsequent periods. The forecasting method of subsequent periods is the same as above.

After derived the predicted value, we need to establish an error formula and evaluate the accuracy of predictions as well,

$$e(k)=\left|\frac{x^{(0)}(k)-\hat{x}^{(0)}(k)}{x^{(0)}(k)}\right|\times 100\ \% \quad (10)$$

where $e(k)$ is the error percentage, $x^{(0)}(k)$ is the raw value, and $\hat{x}^{(0)}(k)$ is the predicted value.

3.3. Back-propagation network

Back-propagation network (BPN) is a kind of well-known artificial neural networks which have applied in many different fields. The BPN algorithm applies the fundamental principle of the gradient steepest descent method to minimize the error function. It compares the outputs of the processing units in the output layer with desired outputs to adjust the connecting weights. The BPN structure is of multi-layer perceptrons, using error back propagation generally, simply known as back-propagation algorithm as the algorithm.

Philip [13] suggested that training the BPN requires the following steps:

1. Select training pair from the training set and apply the input vector of the pair to the network.
2. Calculate the output of the network.
3. Evaluate the error between the network output and the desired output.
4. Adjust the weights of the network in a way that minimizes the error.
5. Repeat steps 1 through 4 for pairs in the training set until the error for the entire set is small enough.

As for the prediction performance evaluation of BPN, the mean absolute percentage error (MAPE) is used as a tool for judging the predictability:

$$MAPE = \frac{\sum_{i=1}^{N} \left| \frac{T_i - A_i}{T_i} \right|}{N} \tag{11}$$

Where T_i is actual value and A_i is prediction value.

3.4. Moving average method

The moving average (MA) is the mean of the previous n data sets. The formula for the simple moving average is

$$F_t = MA(n) = \frac{A_{t-1} + A_{t-2} + \ldots + A_{t-n}}{n} \tag{12}$$

F_t = Forecast for the coming period.
n = Number of periods to be averaged.
A_{t-1} = Actual occurrence in the past period for up to n periods.
$MA(n)$ = The n period of moving average.

4. Case study

This investigation is verified by comparing the predicted demand and actual demand of critical spare parts in an semiconductor factories. This company is one of the leading semiconductor factories in Taiwan. The BGA socket is one of the critical spare parts in this company, which has the characteristics of expensive, large variation of demand, long purchasing lead time and necessary to the operation of machine. Such condition makes the managers difficult to prepare the required number of BGA sockets. Therefore, this investigation will be targeted at the prediction of BGA sockets requirement monthly, and the prediction is carried out using GM(1,1), BPN and MA.

As for data collection, the historical requirements of the BGA sockets and the relevant factors in duration of 28 months from September, 2005 to December, 2007 are collected, the last ten months of BGA sockets requirement will use to compare the prediction accuracy of each forecasting method.

After data collection, this paper applied AHP to find out more influential factors, the questionnaire based on AHP design was distributed to 40 managers and staffs, 33 effective questionnaires were collected. After the weight calculation and analysis base on AHP, the author find out five more relevant factors of BGA sockets requirement, including “The number of ICs tested on machine”, “IC yield rate”, “The loss number of misusage and accident”, “The quality problems of CSP”, and “Month”.

4.1. Moving average method prediction result

This paper used moving average (MA) method to derive the predicted value of BGA requirement, the prediction result of MA also can be regard as foundation to compare the prediction accuracy with other forecasting methods. As consider the length of data, the author used 2 to 18 periods of MA to derive the forecasted value of last ten terms of BGA sockets requirement, and compare the difference with the actual requirement. The average prediction accuracy of the MA is shown as Table 1.

Table 1. The average prediction accuracy of the MA

Moving Average (MA)			
n	Prediction accuracy(%)		Prediction accuracy(%)
2	66.29	11	64.34
3	66.59*	12	65.84
4	62.95	13	66.44
5	61.23	14	66.5
6	62.28	15	66.56
7	60.85	16	66.15
8	60.5	17	66.03
9	61.92	18	65.45
10	62.86	Average accuracy: 64.28%	

n: The number of periods

According to Table 1, the prediction average accuracy of all period of MA is 64.28%, and the prediction accuracy of 3-period of MA is 66.59% which has better predict performance than other periods of MA, the result also indicate that the forecasting of CSP requirement is very difficult, not only because of the large data variation, but also the historical data might not enough to predict future demand accurately.

4.2. Grey prediction result

This investigation utilizes 4 to 6 entry of GM(1,1) to predict the consumption of BGA socket. The reason we utilized 4 to 6 entry of GM(1,1) is according to the 28 months of data length, the GM(1,1) needs least four data sets to predict future situation, and the more entries of GM(1,1) may not indicate better prediction performance. The average prediction accuracy of the GM(1,1) is presented as Table 2.

Table 2. The prediction result of 4,5,6-entry of GM(1,1)

Term	Actural value	4-entry GM(1,1) Predicted value	5-entry GM(1,1) Predicted value	6-entry GM(1,1) Predicted value
19	202	149.06	161.96	150.85
20	194	222.27	226.05	227.62
21	143	244.87	225.01	233.46
22	224	129.9	174.9	177.09
23	184	223.16	194.9	220.83
24	143	223.65	199.47	187.54
25	137	116.24	164.96	160.96
26	139	111.71	106.79	142.62
27	68	135.67	116.86	106.23
28	276	65.3	79.5	78.81
Average Accuracy		55.76%	65.23%	72.74%

The Table 2 shows the 6-entry of GM(1,1) with an average accuracy of 67.42% is higher than 4 and 5 entries of GM(1,1). In this case, the most suitable entry of GM(1,1) is 6. It might imply that when managers decide the demand quantities of BGA sockets, they should consider six months of historical data at least.

4.3. BPN prediction result

This paper also applied BPN to predict the requirement of BGA sockets in last ten terms. However, when the author forecasting the BGA socket requirement of coming term, the values of some relevant factors like “The number of ICs tested on machine”, “IC yield rate”, “The loss number of misusage and accident”, “The quality problems of CSP”,, are all unknown at the prediction timing of coming term, and they will be known until the end of this term. Thus, this paper used the relevant factor’ s data of last term to predict the CSP requirement of coming term, for example, use the relevant factor’ s data of 5^{th} term to predict the BGA sockets requirement of 6^{th} term.

At the training and testing process of BPN, the first 18 data sets are used for training process, and the last 10 data sets are used for testing process. The suitable parameters setting of the BPN is derived by trial and error. The parameters setting and the prediction accuracy of BPN are listed in Table 3.

Table 3. Parameter setting and prediction accuracy of the BPN

Learning Rule: Delta Rule	
Transformation function: Sigmoid Function	
Input nodes	5
Output nodes	1
Number of hidden layer	1
Hidden nodes	2
Initial value of Learning rate	1.0
Decline rate of Learning rate	0.99
Initial value of Momentum rate	0.99
Decline rate of Momentum rate	0.5
Number of training cycle	1000
Average accuracy	66.02%
MAPE	0.3398

According to the Table 3, the average accuracy of BPN is 66.02%, and the MAPE of BPN is 0.3398. The Table 4 presents the prediction accuracy comparison of MA, GM(1,1) and BPN.

Table 4. The highest prediction accuracy of each forecasting method

Forecasting Methods (term)	Average prediction accuracy (%)
MA (3-period)	66.59
GM(1,1)(6-entry)	67.42
BPN	66.02

According to the Table 4, the GM(1,1) (6-entry) have higher average accuracy of 67.42% than BPN and MA, the order from high to low average prediction accuracy of prediction methods is GM(1,1) (6-entry), MA (3-period), BPN. It can be clearly understand when the data sets is few, the data variation is large and the value of some influential factors is unknown at the prediction timing of current term, the GM(1,1) might have better prediction performance than BPN and MA.

5. Conclusions

The critical spare parts in semiconductor industries are considerably expensive, the demand variation is large, the purchasing lead time is long, and indispensably play important roles in factory operation. If the critical spare parts are insufficient, machines may not be able to function, thus resulting in a great risk of slack and waste of resources. Such a situation is more obvious in semiconductor factories. For this consideration, it is important to be able to effectively predict the required number of critical spare parts in advance.

This investigation applied BPN, GM(1,1) and MA to predict the CSP requirement in each term, the author also compare the prediction accuracy between forecasting methods. This paper collected the real data sets of CSP requirement and the data sets of relevant factors from a semiconductor factory in Taiwan, the CSP demand prediction performances of the BPN, GM(1,1) and MA are evaluated in this investigation. The contributions of this paper are interpreted as follows:

(1) This paper examined the prediction performance of BPN, GM(1,1) and MA in small sample size and large variation data of CSP demand. The order from high to low average prediction accuracy of forecasting methods is GM(1,1), MA(3-period), BPN. The GM(1,1) has the higher prediction performance than BPN and MA, the reason might be the data sets variation is too large, and some relevant factor’ s current value is unknown in coming term, so the GM(1,1) is more suitable than BPN and MA for this kind of data sets and problem scenario.

(2) This paper applied the AHP to sieve out more relevant factors corresponding to the demand of CSP in case study, which can help purchasing and inventory managers to make purchasing decision precisely and control the CSP consumption efficiently.

(3)The prediction result of this paper can be provided as a reference of inventory and ordering strategies of CSP, the managers can refer to the forecasting requirement of CSP to reduce the slack risks and unnecessary costs.

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